Neural Networks and Cascade Modeling Technique in System Identification

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Abstract. The use of the Middle East Technical University Neural Network and Cascade Modeling (METU-NN-C) technique in system identification to forecast complex nonlinear processes has been examined. Special cascade models based on Hammerstein system modeling have been developed. The total electron content (TEC) data evaluated from GPS measurements are vital in telecommunications and satellite navigation systems. Using the model, forecast of the TEC data in 10 minute intervals 1 hour ahead, during disturbed conditions have been made. In performance analysis an operation has been performed on a new validation data set by producing the forecast values. Forecast of GPS-TEC values have been achieved with high sensitivity and accuracy before, during and after the disturbed conditions. The performance results of the cascade modeling of the near Earth space process have been discussed in terms of system identification.

1 Introduction

Most of the dynamical systems can be represented by nonlinear modeling techniques. Nonlinear modeling is capable of describing the global system behavior for the overall operating range. Applying nonlinear model identification is inevitable for most of the real complex nonlinear processes including the near Earth space processes.

For many nonlinear dynamic processes, cascade models based on Hammerstein system modeling provide sufficient approximation [1] [2] [3] [4] [5] [6]. For many nonlinear dynamic processes it is required to present nonlinearities in the gain of the processes and provide dynamics in a linear block. This can be achieved by cascade modeling. In Hammerstein system modeling a nonlinear static block is cascaded with a linear dynamic block as shown in Figure 1.

These types of dynamic nonlinear process modeling provide some important features. The process identification task is simplified by modeling the dynamic part in the linear block, so data collection, computation of parameters and dynamic system

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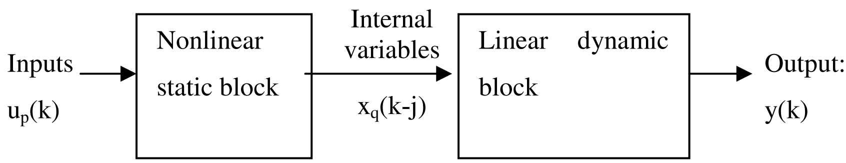

Fig. 1. Cascade models based on Hammerstein system modeling

analysis are simplified. To present nonlinearity in only the static gain decreases the degrees of freedom in the nonlinear system identification. In addition to this, it has accurate and robust approximations for a large class of real complex processes [1].

The internal variables are state-like variables and they are estimated by METU-NN. The static nonlinearity and the dynamic linearity in METU-C are estimated by using the cascade modeling technique.

It is important to identify ionospheric parameters, because satellites in low Earth orbit travel through it, and it is the medium through which radio waves used for communications propagate. Forecasting the number of electrons in a column of one meter-squared cross-section along a path through the ionosphere [7], the total electron content (TEC) values, is vital for telecommunications and satellite based navigation systems especially in the disturbed space weather conditions [8] [9] [10]. The interaction between electromagnetic waves and the ionospheric plasma has been studied both from scientific and engineering points of view [11]. Since 1990 a group of aerospace and electrical engineers have been developing Near Earth Space data driven models for system designers, users, planners as part of the EU-COST-TIST Actions at the METU [12]. The authors have studies on Neural Network based approaches, in modeling of the ionospheric processes [8] [9] [12] [13] [14] [15] [16] [17]. Those studies have provided insight on the system identification of the near Earth space processes.

In this work, to the best knowledge of the authors, it is the first time special models based on Hammerstein system modeling, METU-NN-C, with significant inputs have been developed for near Earth space processes. This paper outlines TEC forecasting problem and preparation of data, explains the METU-NN-C Hammerstein models as a system identification approach for forecasting ionospheric processes, gives the results with error tables, cross correlation coefficients and scatter diagrams, and discusses the generalized and fast learning and operation of the METU-NN-C Models.

2 Preparation of Data

For the training, test and validation within the development mode of the METU-NN-C, TEC data evaluated from GPS measurements in 1 April – 31 May 2000 and 2001 at Chilbolton (51.8° N; 1.26° W) receiving station are used. Operation has been performed on another data set by producing the forecast TEC values at Hailsham (50.9° N; 0.3° E) GPS receiving station for selected months in 2002 [18].

In the model intrinsic information about the solar activity is achieved by choosing the time periods for input data with the similar solar activity. This is the basic criterion in the selection of the train, test and validation years. The current high solar activity time periods are selected in the time intervals. For training and validation phases within development procedure data sets of same month but different year are used to take the seasonal dependency into account.

3 Construction of the Neural Network Model

In METU-NN, for the current process, Feedforward Neural Network architecture with six neurons in one hidden layer is used. The activation functions in the hidden layer are hyperbolic tangent sigmoid functions and the activation function in the output layer is a linear function, so that the hidden layer outputs can represent the static part of the state-like internal variables in cascade modeling. Levenberg-Marquardt Backpropagation algorithm is used during training [19] [20]. The METU-NN is used to estimate the internal variables. The 5 inputs used for the METU-NN are as follows:

1. The present value of the TEC:

$$u_1(k) = \mathrm{f(k)} \tag{1}$$

2. Cosine component of the minute, *m*, of the day:

$$u_2(k) = C_m = -Cos(2.\pi.m / 1440) \tag{2}$$

3. Sine component of the minute of the day:

$$u_3(k) = S_m = Sin(2.\pi.m / 1440) \tag{3}$$

4. Cosine component of the day, *d*, of the year:

$$u_4(k) = C_d = -Cos(2.\pi.d / 366) \tag{4}$$

5. Sine component of the day of the year:

$$u_5(k) = S_d = Sin(2.\pi.d / 366) \tag{5}$$

The output layer of the METU-NN hosts the value of the TEC being observed 60 minutes later than the present time. The outputs of the hidden layer in METU-NN are six of the internal variables for the METU-C.

4 Construction of the Cascade Model

The static nonlinearity in METU-C is described by polynomial representation of inputs. If the inputs are denoted by $u_p(k)$ then the outputs of the nonlinear element, i.e. the internal variables $x_q(k)$, may be expressed as in Equation 6.

$$\hat{\hat{x}}_q(k) = \sum_{p=1}^{R} f\left[u_p(k)\right] = \sum_{p=1}^{R} \sum_{i=0}^{m} \gamma_{pi} . u_p^i(k) \tag{6}$$

where R is the number of inputs, m+1 is the length of the series and γ_{pi} are coefficients to be determined.

The output $u_1(k+1)$ is represented as shown in Equation 7 by using a dynamic linearity by optimizing a linear relationship for the internal variables $x_q(k)$ and their past values $x_q(k-j)$ which constitute their history.

$$\hat{\hat{u}}_1(k+1) = \sum_{q=1}^{S}\sum_{j=0}^{n} h_q(j).\hat{\hat{x}}_q(k-j) \tag{7}$$

where S is the number of the static internal variables and n is the number representing the history of the stored internal variables in memory. Thus, the product S.(n+1) gives the number of dynamic internal variables. The coefficients of the linearity in Equation 7, i.e. $h_q(j)$, are also determined in the development mode.

In the development mode, the construction work of the METU-C is carried out. It is composed of "training phase" and "test phase" as in the Neural Network approach [21]. In the training phase the parameters of the cascaded static nonlinear block and dynamic linear block are optimized. Figure 2 demonstrates the development modes of the METU-NN-C blocks.

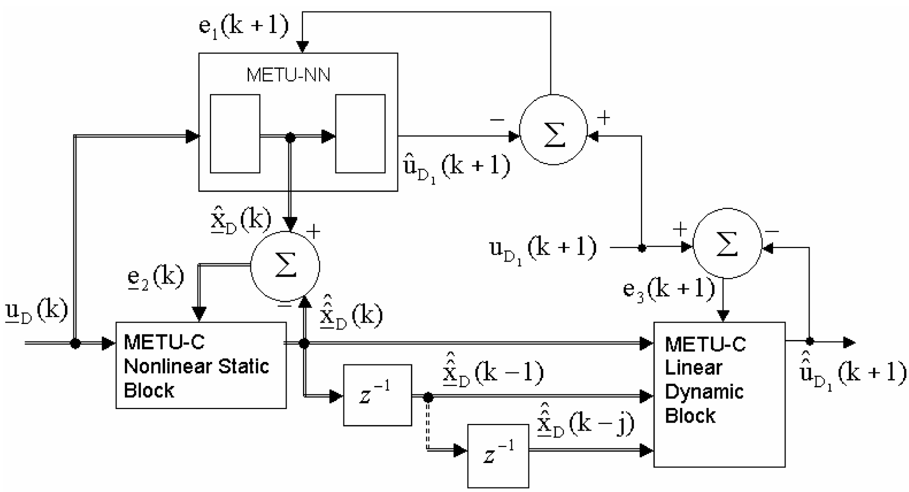

Fig. 2. Development of the METU-NN-C Models

The "Levenberg-Marquardt" optimization algorithm is used within training in the development mode for fast learning of the process with input data of very large size. For preventing the memorization, independent validation data are used and when the gradient of the error in the validation phase becomes near zero the training is terminated. The model is then ready for its use in the operation mode for forecasting of the TEC values. In the operation mode another data set is used for calculating the errors, point by point, to measure the performance of the model. Figure 1 demonstrates the operation mode of the METU-C.

For considering the first, second and third order terms in the polynomial representation, m is selected to be 3 for the TEC input, i.e. m=3 for p=1 in the model. For the temporal inputs m is selected to be 1, i.e. m=1 for p>1 in the model. Let the time instant *k* be in terms of minutes. The value of the TEC at the time instant *k* is designated by f(k). The 7 inputs used for the METU Cascade Model are the present value of the TEC, second and third powers, Cosine and Sine components of the minute of the day and day of the year.

The outputs of the first stage, i.e. 6 outputs for the static nonlinear block designated by $x_q(k)$, and their one hour past and two hours past values are stored as internal variables so that S=6 and n=2 in Equation 7. These internal variables are the inputs to the second stage of the cascade model, i.e. 18 inputs for the dynamic linear block of the METU-C model.

The output of the cascade model is designated by $u_1(k+60)=f(k+60)$ which is the value of the TEC to be observed 60 minutes later than the present time.

5 Results

In performance analysis an operation has been performed on an independent validation data set by producing the forecast values of the TEC. The operation mode performance analyses and results of the TEC forecast cover the time interval between April and May 2002 for the Hailsham receiving station. Forecast of the TEC values one hour in advance is performed for the validation data set in 10 minutes interval. Then the cross correlation coefficients between the observed GPS TEC and forecast TEC are calculated. The root mean square, normalized and absolute error values are also calculated. Table 1 is the error table displaying the results.

Table 1. Error Table

Root Mean Square Error (TECU)	1.7908
Normalized Error	0.0639
Absolute Error (TECU)	1.1708
Cross Correlation Coefficient	0.9863

Figure 3 is the scatter diagram of the forecast and observed TEC values. Figure 4 is the enlarged portion of some data points, i.e. the diurnal variations of the observed and forecast TEC values during 18-22 April 2002.

In the scatter diagram the fitted line has a slope close to one. Therefore the forecasting errors are small. This fact is the indication of the system reaching the correct operating point within the system identification. In other terminology, the system is succeeded to reach the global minimum of the error cost function. The correlation coefficients are very close to unity, which means that the METU-C model learned the shape of the inherent nonlinearities. Therefore, the deviations from straight line are small in the scatter diagram. When Figure 4 is observed it can be concluded that the model gives accurate forecasts before, during and after the disturbed conditions.

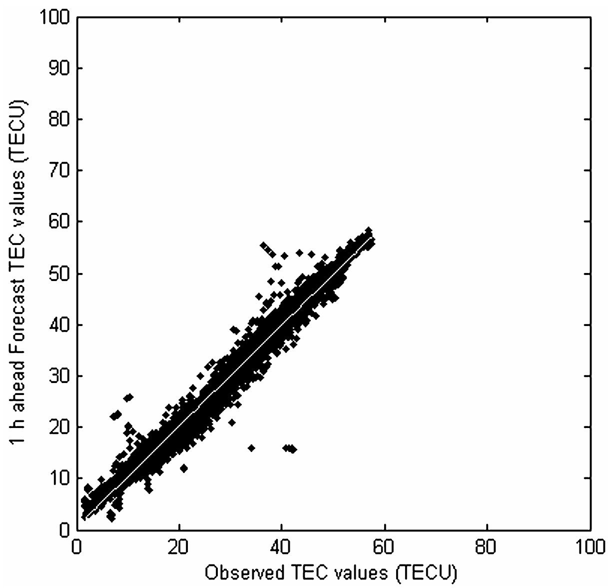

Fig. 3. 1 hour ahead Forecast TEC versus Observed GPS TEC values for April and May 2002

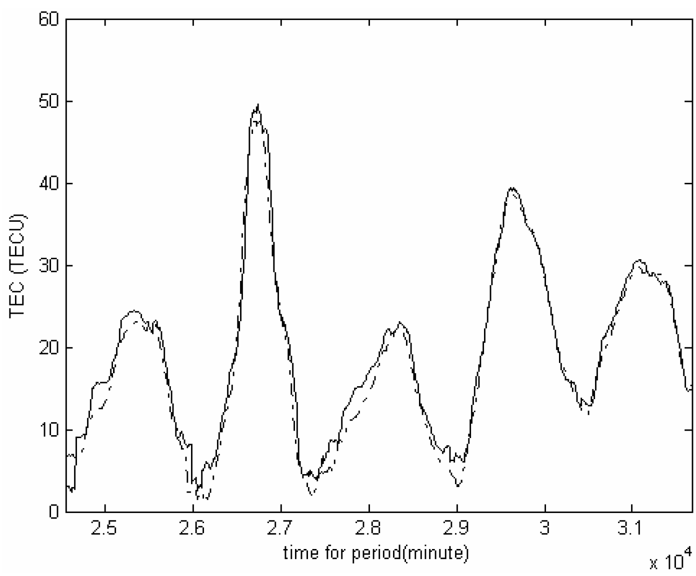

Fig. 4. Observed (dotted), and 1 hour ahead Forecast (solid) TEC values for 18-22 April 2002

6 Conclusions

Forecasting of the TEC values, especially in the disturbed space weather conditions, is crucial for communication, radar and navigation systems employing HF radio waves to cope with the effects of unpredictable variability of the ionospheric parameters.

Neural Network and cascade modeling technique in METU-NN-C are used in system identification. In this work, to the best knowledge of the authors, cascade modeling of Hammerstein form has been used first time for the forecast of an ionospheric-plasmaspheric process, namely the TEC variation 1 hour in advance. The model learned the shape of the inherent nonlinearities and the system reached the correct operating point. The cascade modeling of the process is also capable of forecasting the TEC values for disturbed solar-terrestrial conditions.

It is demonstrated that the identification of the complex nonlinear processes, such as the TEC variation, can be achieved by cascading a static nonlinear block and a linear dynamic block of Hammerstein form.

Summary of the main contributions of this work may be given as follows:

1) Organization of representable data for learning complex processes,
2) Estimation of the internal variables of METU-C by using NN,
3) Cascade modeling of a highly complex nonlinear process such as the TEC variation, and
4) General demonstration of learning capability by calculating cross correlations and general demonstration of reaching a proper operating point by calculating errors.

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